EMG Signal Analysis By Using Various Wavelet And A Comparative Study

Saleh Ahmed
Dept. Computer Science and Engineering,
Bangabandhu Sheikh Mujibur Rahman Science and Technology University, Gopalganj-8100, Bangladesh.
sumon.edu@gmail.com

Mahboob Qaosar, Dr. Shamim Ahmad
Dept. Computer Science and Engineering,
University of Rajshahi, Rajshahi, Bangladesh
qaosar@ru.ac.bd, shamim_cst@ru.ac.bd

***Abstract*— Electromyography (EMG) signals can be utilized for clinical/biomedical treatments, Evolvable Hardware Chip (EHW) development and modern Human-Computer Interaction. EMG signals collected from muscles need advanced approaches for detection, decomposition, processing, and classification. For properly investigate EMG signal, there requires a good quality of decomposition so that it can exhibit the total characteristics of EMG signals. The EMG signal is a Non-Stationary signal; therefore, it needs such a way which is suitable for decomposing non-stationary signal as a result, wavelet decomposition is an excellent choice. There are various kinds of wavelet available. Henceforth, it is necessary that proper attempts should be considered to determine the suitable one. Here the analysis of EMG Signals was made by different wavelet decomposition approach with various kinds of wavelets and represented the comparative study on based on the best possible energy localization in the time-scale plane.**

Keywords—EMG Signal Analysis, Signal Decomposition, Wavelet Decomposition, Non-Stationary Signal.

I. INTRODUCTION

The biomedical signal means a composite electrical signal acquired from any organ that represents a physical variable of interest. This signal is usually a function of time and is describable in terms of its amplitude, frequency and phase [1]. The EMG signal is a biomedical signal that measures electrical currents generated in muscles during its contraction and represents a neuromuscular activity. The nervous system always regulates muscle action (contraction/relaxation). The EMG signal is a complex signal, which is controlled by the nervous system and is dependent on the different anatomical and physiological properties of muscles. The muscles that are attached to a single neuron is called MU (Motor Unit). The shapes and firing rates of Motor Unit Action Potentials (MUAPs) in EMG signals provide a vital source of information for the diagnosis of neuromuscular disorders.

Once suitable algorithms and methods for EMG signal analysis are available, the type and properties of the signal can be appropriately understood, and hardware implementations can be obtained for various EMG signal related applications. For acquiring proper information, it requires to decompose the signal appropriately. EMG signal is a combination of many MUAP which have shape varies with the various anatomical and physiological properties of muscles, so it acts like a non-stationary signal. In wavelet analysis, a signal considers as a shifted and scaled version of the wavelet, in the case of EMG signal it is a combination of MUAP. So, if we choose a wavelet and the shape of wavelet is close to MUAP of an EMG signal, then it can be successfully decomposed by the wavelet. We can also find the nature of the signal from the analysis [1], i.e. is it from a healthy functional muscle or malfunctioning one? In this paper, we focused on the decomposition of various EMG signal with different wavelets and drew a comparative study of the decomposition based on the best possible energy localization in the time-scale plane.

II. MUSCLE AND EMG SIGNAL

Muscle tissue carries electrical potentials like the way nerves do and the name provided to these electrical signals in the muscle action potential. Surface EMG is a process of recording the information which is available in these muscle action potentials (Fig. 1.).

Two varieties of electrodes have been utilized to acquire muscle signal: invasive electrode and non-invasive electrode. When EMG is obtained from electrodes on the skin, all the muscle fiber action muscles underlying the epidermis potentials occur at irregular intervals. So, at any time, the EMG signal may be either positive or negative voltage when specific muscle wire or needle directly in the muscle. The aggregate of action potentials from all the muscle fibers of a single motor unit action potential (MUAP) is detected by an electrode (non-invasive) located near this field, or by a needle electrode (invasive) inserted in the muscle.

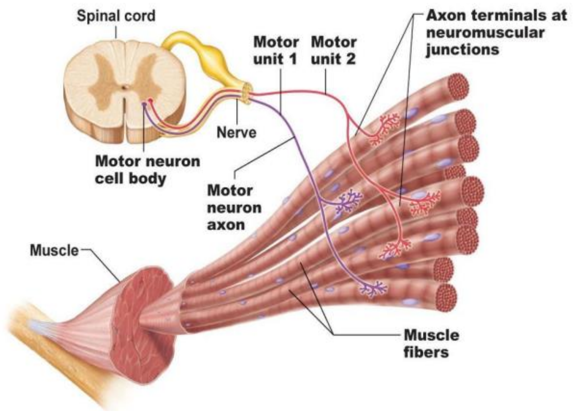

Fig. 1. Motor Unit and Muscle

$$x(n) = \sum_{r=0}^{N-1} h(r)e(n-r) + w(n) \quad (1)$$

Equation (1) presents a simplistic model of the EMG signal; where, x(n), modelled EMG signal, e(n) represents the firing impulse, h(r) expresses the MUAP[4], w(n) describes zero mean additive white Gaussian noise and n is the number of motor unit firings.

The signal is acquired up at the electrode and amplified. Typically, a differential amplifier is used as a first stage amplifier. Supplementary amplification stages may assist before being displayed or stored, or cancel high-frequency noise, or cancel other possible artefacts. Frequently, the user is interested in the amplitude of the signal. Consequently, the information is usually reformed format to indicate EMG amplitude.

The nervous system is both the regulation and communications system of the body. This system consists of a high number of associated sensitive cells called neurons that interact with various parts of the body through electrical signals, which are rapid and distinct. The nervous system consists of three main parts: the brain, the spinal cord and the peripheral nerves. The neurons are the fundamental structural part of the nervous system and vary considerably in size and shape. Neurons are highly specialized cells that carry information in the form of nerve impulses from one portion of the body to another.

A muscle is made of bundles of specialized cells capable of contraction and relaxation. The principal function of these specialized cells is to produce forces, actions and the ability to communicate such as speech or writing or other modes of emotion. Muscle tissue has extensibility and elasticity. It can get and react to stimuli and can be shortened or contracted. Muscle tissue has four vital functions: producing motion, moving substance within the body, providing stabilization, and generating heat. Three varieties of muscle tissue can be identified based on formation, contractile characteristics, and control mechanisms: (i) skeletal muscle, (ii) smooth muscle, and (iii) cardiac muscle. The EMG is applied to the study of skeletal muscle. The skeletal muscle tissue is connected to the bone, and its contraction is responsible for supporting and moving the skeleton. The contraction of skeletal muscle is begun by impulses in the neurons to the muscle and is generally under voluntary control. Skeletal muscle fibers are well-supplied with neurons for their contraction. This neuron is called a "motor neuron", and it approaches close to muscle tissue but is not connected to it. One motor neuron typically supplies stimulation to multiple muscle fibers.

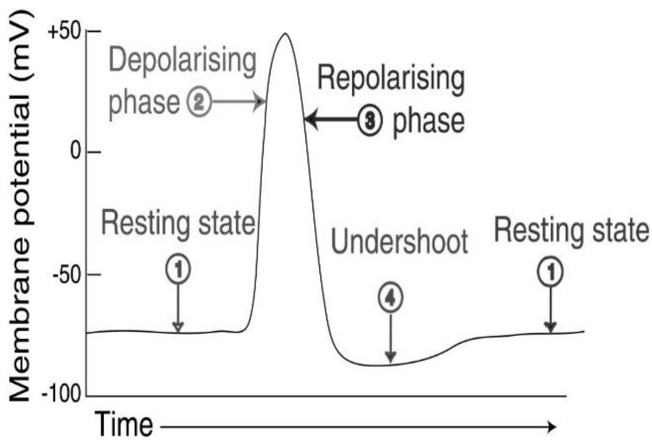

Fig. 2. Typical MUAP

The human body is electrically neutral; it has the same number of positive and negative charges. But in the resting state, the nerve cell membrane is polarized due to differences in the concentrations and ionic composition across the plasma membrane. A potential difference exists between the intracellular and extracellular fluids of the cell. Electrode set on muscles can then sense it.

III. EMG Signal Decomposition

The method of sorting out the individual MUAP trains in an EMG signal is called EMG decomposition. Since each MUAP is related in a one-to-one way with the release of a motoneuron, EMG decomposition gives a unique way to observe the operation of individual motoneurons in the entire human nervous system. Also, since the patterns of the MUAPs carry information about the properties and arrangement of the muscle fibers, EMG decomposition producing a novel way to study motor-unit organization in intact human muscles. This information is also used in clinical neurophysiology for diagnosing neuromuscular diseases. Of course, some signals, and some MUAP trains inside those signals can be decomposed more reliably than others. Decomposability depends on various factors including the complexity of the signal, the level of environmental noise, the variability of the MUAPs from the same motor units, and the similarity of the MUAPs from various motor units. Some signals can be decomposed with a high degree of confidence, while others cannot be reliably decomposed at all.

IV. Wavelet Analysis and EMG Signal

Wavelets are an excellent tool for biomedical signal analysis. Wavelets are utilized for the study of signals that are non-stationary and is time varying in characteristics. The EMG signal carries transient signals linked to muscle movement. EMG signals have typically multiple temporary components (MUAP), which are very impressive to separate and classify according to their physiological importance. A wavelet-based decomposition is a vital tool for analyzing EMG signal; The EMG signal is decomposed in various levels (resolution) of the wavelet [5]. The noisy elements of the wavelet decomposition are pruned, and the signal is rebuilt from the remaining. The rebuild de-noised signals exhibit muscle action.

The wavelet transform (WT) is a useful analytical tool for the study of non-stationary and fast transient signals. One of the principal characteristics of WT is that it can be applied for a discrete time filter bank. The Fourier transforms of the wavelets are mentioned to as WT filters. The WT serves a very suitable technique for the analysis of EMG signals.

Guglielminotti and Merletti [12] theorized that if the wavelet is chosen so as to match the shape of the MUAP, the resulting WT produces the best possible energy localization in the time-scale plane. Based on the study, Laterza and Olmo [8] concluded that the WT is especially useful for MUAP discovery in the presence of additive white noise. In this circumstance, the noise participations are disseminated over the whole-time scale plane, independently of the wavelet applied.

In 1999, Pattichis and Pattichis [9] found that the WT could also be applied to examine signals at various resolution levels. According to the method, the process of analyzing signals at multiple resolution level is known as multiresolution analysis. They explained the relationship between wavelet coefficients and the time-frequency plane.

$$f^0(t) = \sum_k x_k \phi(t-k) \tag{2}$$

The WT algorithm consists of the decomposition stage and regeneration stages. Pattichis and Pattichis shortly describe how factors from each step of the WT can be applied to create a functional approximation to the original signal. Given signal samples, x0, x1, x2..., the constructed continuous time signal is given by equation (2)

Where ø(t-k) is described as a scaling function, this implies that the signal samples are weighted means of the continuous signal. Again in 2003, Kumar appeared with a related kind of scheme saying that the WT decomposes a signal into different multiresolution elements according to a basis function called “wavelet function” (WF). The WF is both dilated and translated in the time offering a two-dimensional cross-correlation with the time domain SEMG signal. This approach can be seen as an analytical microscope that gives a mechanism to identify and characterize a short time segment within a nonstationary signal. It is the procedure that gives information linked to the time-frequency variation of the signal.

Kumar also decided that the Short Fourier Transform (SFT) with the comparatively short time intervals can try to trace spectral difference with time but does not select an optimal time or frequency resolution for the nonstationary signal. SEMG has been decomposed performing WT with different WF, and the output of the power transform domain is calculated and applied as the deciding parameter in determining the WF that exhibits the biggest difference between SEMG cases.

V. Shape of MUAP

A muscle can generate MUAP in various shape based on the neuromuscular change in a muscle.

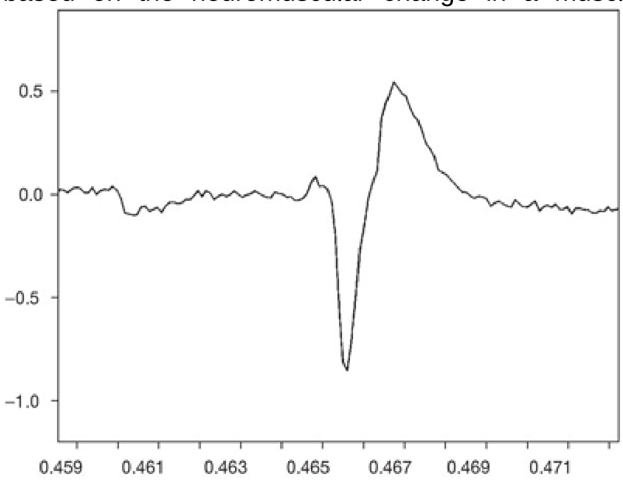

Fig. 3. MUAP from the medial thyroarytenoid muscle of a healthy adult larynx.

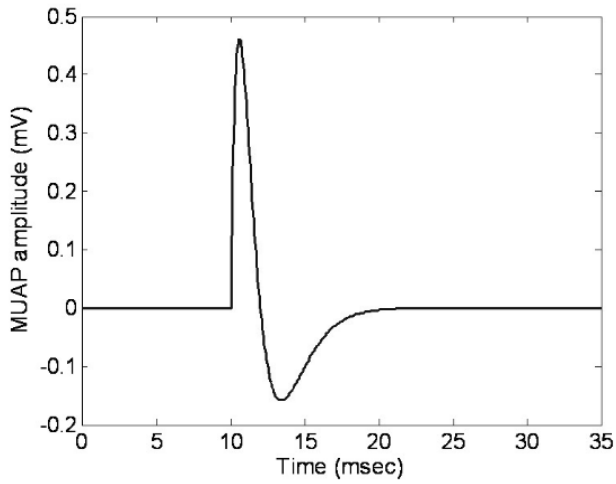

Fig. 4. MUAP from the malfunctioned muscle

For example, Fig. 3. shows a MUAP from the medial thyroarytenoid muscle of a healthy adult larynx. On the other hand, Fig. 4. shows a MUAP from the malfunctioned muscle.

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VI. DIFFERENT WAVELET AND SHAPE OF WAVELET

Various types of wavelets are available. The shape and properties of some common wavelets are given bellow-

A. *Daubechies Wavelets*

Daubechies wavelet (Fig. 5.) compactly supported wavelets with external phase and highest number of vanishing moments for a given support width. Associated scaling filters are minimum-phase filters.

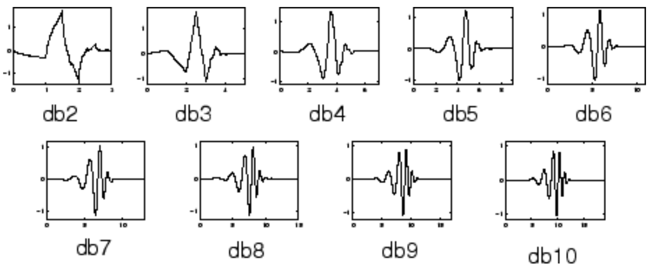

Fig. 5. Various Daubechies Wavelets

B. *Symlets Wavelets*

Symlets Wavelets (Fig. 6.) compactly supported wavelets with least asymmetry and highest number of vanishing moments for a given support width. Associated scaling filters are near linear-phase filters.

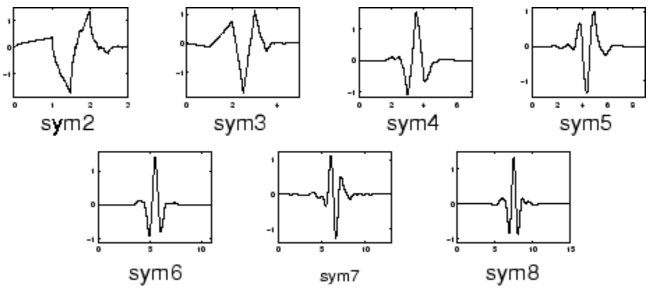

Fig. 6. Various Symlets Wavelets

C. *Coiflets Wavelets*

Coiflets Wavelets (Fig. 7.) compactly supported wavelets with the highest number of vanishing moments for both phi and psi for a given support width.

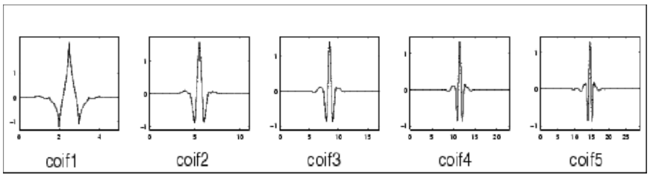

Fig. 7. Various Coiflets Wavelets

D. *Mexican Hat Wavelet*

Mexican Hat Wavelet (Fig. 8.) second derivative of the Gaussian probability density function.

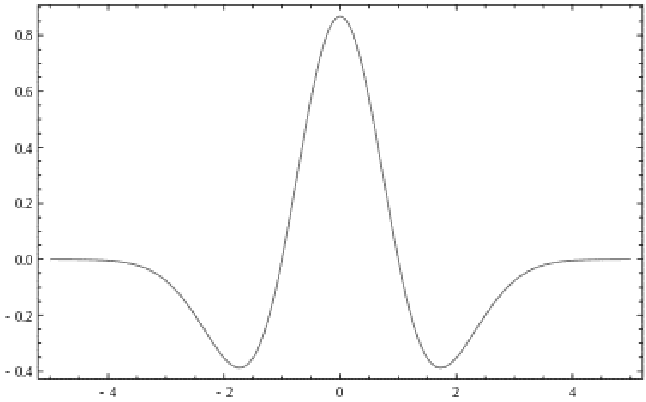

Fig. 8. Mexican hat Wavelets

$$mexh(t) = \frac{2}{\sqrt{3\sigma}\pi^{\frac{1}{4}}}(1-(\frac{t}{\sigma})^2)e^{-\frac{t^2}{2\sigma^2}}$$

E. *Morlet Wavelet*

Morlet Wavelet (Fig. 9.) expressed by the following Equation

$$morl(x) = e^{-\frac{x^2}{2}}\cos(5x)$$

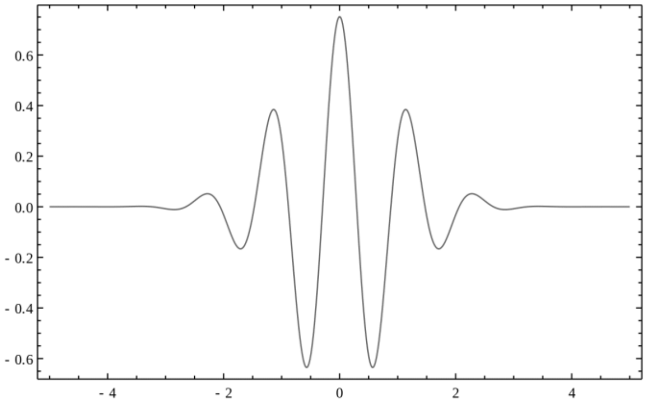

Fig. 9. Morlet Wavelets

VII. ALGORITHM

Both the time and frequency domain approaches have been attempted in the past. The wavelet transform (WT) is an efficient mathematical tool for local analysis of non-stationary and fast transient signals. One of the main properties of WT is that it can be implemented by means of a discrete-time filter bank. The Fourier transforms of the wavelets are referred to as WT filters. The WT represents a very suitable method for the classification of EMG signals.

Guglielminotti and Merletti [12] theorized that if the wavelet analysis is chosen so as to match the shape of the MUAP the resulting WT yields the best possible energy localization in the time-scale plane. So, the shape of the wavelet and MUAP is closely related to better decomposition. This is the key idea of this analysis.

In this algorithm, we decompose signal using DWT for different wavelet and calculate possible energy localization in time scale plane. Then determine the best one that gives the best energy localization for a signal and suggests that the MUAP shape in this signal may like the shape of the MUAP signal. For any disease or neuromuscular disorder if the normal shape is changed the amount of change as well as the shape of the present MUAP also can be determined by using proper wavelet.

VIII. Working Process

EMG Signal is decomposed with Wavelet technology. The block diagram (Fig. 10.) of the procedure given bellow

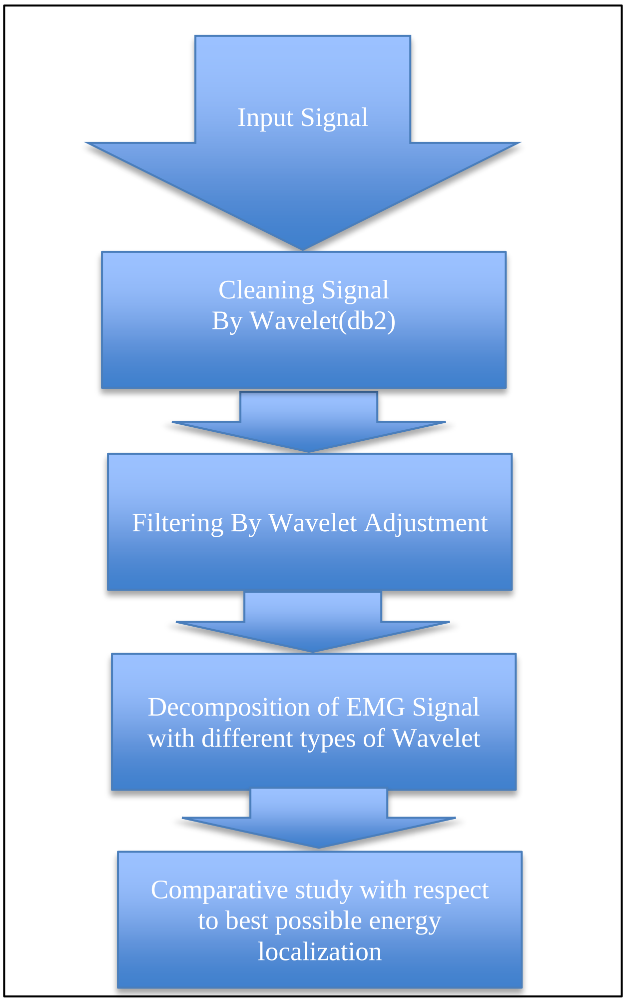

Fig. 10. EMG Signal is decomposed with Wavelet technology

At first, noises were cleaned by db2 wavelet and taken the approximation signal as a clean signal. Next filter by wavelet adjustment low pass filter then this signal is used for decomposition and detection. Finally, the signal was decomposed by various wavelet that support low-frequency signal decomposition and a comparative study was shown here based above algorithm.

IX. Result and Analysis

The following (Fig. 11. and Fig. 12.) shows energy localization in time scale plane of EMG signal decomposed by different wavelets.

Wavelet	Energy localization in the time-scale plane (ev)
Haar	2.08E-05
db2	1.50E-02
db3	2.70E-01
db4	4.96E+02
db5	9.48E+02
db6	5.51E+02
db7	4.79E-01
db8	1.46E-01
db9	6.52E-01
coif1	2.11E-02
coif2	2.96E-01
coif3	1.60E-02
coif4	5.16E-01
coif5	1.00E+00
sym2	5.60E-01
sym3	1.00E+02
sym4	6.46E+01
sym5	2.26E+01
sym6	1.00E+02
sym7	1.00E+02
sym8	1.00E+02

Fig. 11. Energy localization in time scale plane of EMG signal decomposed by different wavelets

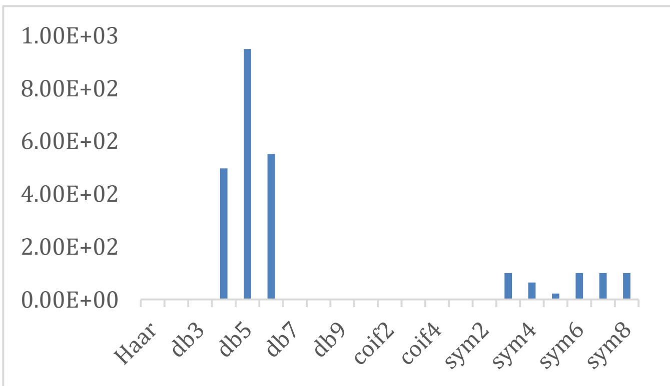

Fig. 12. Energy localization in time scale plane of EMG signal decomposed by different wavelets

From the Fig. 11. and Fig. 12., MUAP generated from muscle are not responding in a similar way when decomposed by various wavelets. The wavelet close to the shape of MUAP in an EMG signal will produce more energy localization in the time-scale plane. Therefore, EMG signal disintegration by the wavelets shows different energy localization in time scale plane. This type of energy variation can be used for classifying different EMG signal.

X. Conclusion

In this work, EMG signals are denoised and decomposed using various wavelet and energy localization in time scale plane is computed. It is found that this energy localization for different EMG signals is not similar. This energy localization of EMG signal can be used classify the EMG signal generated from different gesture and functionalities. For future direction, classification of the EMG signal will be done using the energy localization pattern.

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